JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Enhancing Sarcasm Recognition Using Chicken Swarm Optimization Algorithm with Graph Neural Network on Social Media

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Abstract

Sarcasm recognition on social networking media presents a challenging yet critical task in natural language processing (NLP). Given the contextual nuances and inherent subtleties of sarcasm, machine learning (ML) approaches are exploited to decipher sarcastic intent in textual content. This model often leverages sentiment analysis, context-aware features, and linguistic cues to discriminate between sarcastic expressions and literal statements. Advancements in ML approaches, especially those integrating deep learning (DL) techniques and contextual embeddings, continue to refine sarcasm detection techniques, facilitating contextually aware and more nuanced interpretation of language in the dynamic landscape of social networking media interaction. This study proposes a groundbreaking approach to improve sarcasm recognition by integrating the Chicken Swarm Optimization Algorithm (CSOA) with Graph Neural Network (GNN), named CSOA-GNN model. Firstly, data pre-processing takes place and TF-IDF is exploited for word embedding, which captures the distinct features of sarcastic language in a vectorized representation. Then, the GNN is applied for classification, using its capability to capture contextual relationships and dependencies amongst words in sentences, thus enhancing the model's sarcasm detection performance. Furthermore, CSOA is introduced for parameter tuning, improving the GNN's hyperparameter to refine its performance. The proposed method shows promising outcomes, demonstrating the efficiency of synergizing GNN-based classification, CSOA-based parameter tuning, and TF-IDF word embeddings for improved sarcasm detection in the dynamic context of social media interaction. This new integration contributes to the development of NLP technique for better understanding and interpretation of sarcasm in online interaction.

Keywords: Sarcasm Recognition; Social Media; Chicken Swarm Optimization; Natural Language Processing; Deep Learning; Word Embedding

1. Introduction

Sarcasm denotes the words that are utilized in order to hurt somebody to express your anger or to create things humorous [1]. It is one of the ways to deliver your negative approaches in positive or funny words. In present scenario, Twitter is the leading and largest social platform where several persons express their opinions, approaches or activities in the method of tweets, which occasionally can be sarcastic [2]. To examine and identify this sarcasm on Twitter platform, we will construct ML techniques utilizing neural networks for sarcasm recognition [3]. The issue of sarcasm recognition is most challenging because it includes a difficult relationship of linguistic, contextual and pragmatic factors. Sarcasm can be conveyed in numerous methods which range from subtle to overt, and can rest on a range of contextual and linguistic cues [4]. For instance, sarcasm can be sent utilizing understatement, exaggeration, parody or irony and can include a collection of linguistic features like negation, presupposition and lexical ambiguity [5].

Ranges of machine learning (ML) models are useful for sarcasm recognition tasks such as support vector machines, random forest, convolutional neural network (CNN), naive Bayes and recurrent neural network (RNN) [6]. These techniques function by learning to identify designs in text data that are related to sarcasm. Also, the choice of feature is a significant aspect of sarcasm recognition [7]. Numerous features have been employed for sarcasm recognition such as semantic, syntactic and lexical features [8]. Lexical features contain the frequency of definite words that are frequently linked with sarcasm, whereas syntactic features include the usage of parts of speech and other grammatical structures to identify sarcasm [9]. Semantic features comprise the usage of word embedding or other models to capture the text meaning [10].

In [11], the author concentrates on spotting sarcasm in written talks from numerous social networks and online media platforms. To finish this, the author proposed a DL method utilizing multi-head self-attention and gated recurrent unit (GRU). The GRU absorb longer-range dependences among these cue words to categorize the input text in better way, and the multi-head self-attention unit helps to classify critical sarcastic cue arguments from an input. Ren et al. [12] present a multi-level memory system employing sentiment semantics to pick up the features of sarcasm words. The author employs the first and second level- memory system to take sentiment semantics and the differences among sentiment semantics and the condition in every sentence. Furthermore, the author employs an enhanced CNN to recover the network of memory in the lack of local data. Ashok et al. [13] presented a unique deep neural networks (DNNs) method where Bidirectional Long-Short Term Memory (Bi-LSTM) endure Hyper parameters optimizer utilizing genetic system tracked by a CNN for sarcasm recognition.

Pandey et al. [14] developed a hybrid attention-based LSTM (HA-LSTM) system to detect sarcastic reports. The HA-LSTM is dissimilar to the current LSTM method, as the projected HA-LSTM system contains sixteen diverse linguistic features. Hao et al. [15] projected a Contextual Sarcasm Detection Method (CSDM) by demonstrating improved semantic symbols with consumer profile and forum topic data, where a user-forum fusion and context-aware attention system have been employed to get various representations from separate features.

This study proposes a groundbreaking approach to improve sarcasm recognition by integrating the Chicken Swarm Optimization Algorithm (CSOA) with Graph Neural Network (GNN), named CSOA-GNN model. Firstly, data pre-processing takes place and TF-IDF is exploited for word embedding, which captures the distinct features of sarcastic language in a vectorized representation. Then, the GNN is applied for classification, using its capability to capture contextual relationships and dependencies amongst words in sentences, thus enhancing the model's sarcasm detection performance. Furthermore, CSOA is introduced for parameter tuning, improving the GNN's hyperparameter to refine its performance. This new integration contributes to the development of NLP technique for better understanding and interpretation of sarcasm in online interaction.

2. The Proposed Method

In this paper, we have presented an innovative approach to enhance sarcasm recognition by integrating the CSOA-GNN model. The CSOA-GNN technique's main purpose is to contain different processes namely data preprocessing, GNN-based classification, and CSOA-based parameter tuning. Fig. 1 represents the entire procedure of CSOA-GNN algorithm.

2.1. Preprocessing

Initially, data pre-processing takes place and TF-IDF is applied for word embedding. The text data undergoes various steps of preprocessing, the textual data is standardized, cleaned, and transformed into an appropriate form for the analysis and feature extraction [16]. During the preprocessing stage, the following steps are included: Lowercasing: Each text is transformed into lowercase to ensure consistency. Cleaning up: this operation is implemented for removing redundant elements from the text and deleting special characters, URLs, and punctuation marks (# hash character), specific to platforms such as Twitter. Replacing: Certain textual element is replaced with their simplified forms or related words. This includes contraction with the extended word, transforming emoji to their relevant words, and decreasing repetitive character occurrences to a single occurrence. Tokenization: The cleaned texts are split into individual words or tokens for creating a tokenized representation and help with further analysis and processing. Lemmatization/Stemming: each token is processed through the lemmatization or stemming process. The objective is to convert the token into its root or base form, such as transforming the token ”interesting” into” interest.” Stemming includes reducing the token to stem form by eliminating suffixes or prefixes.

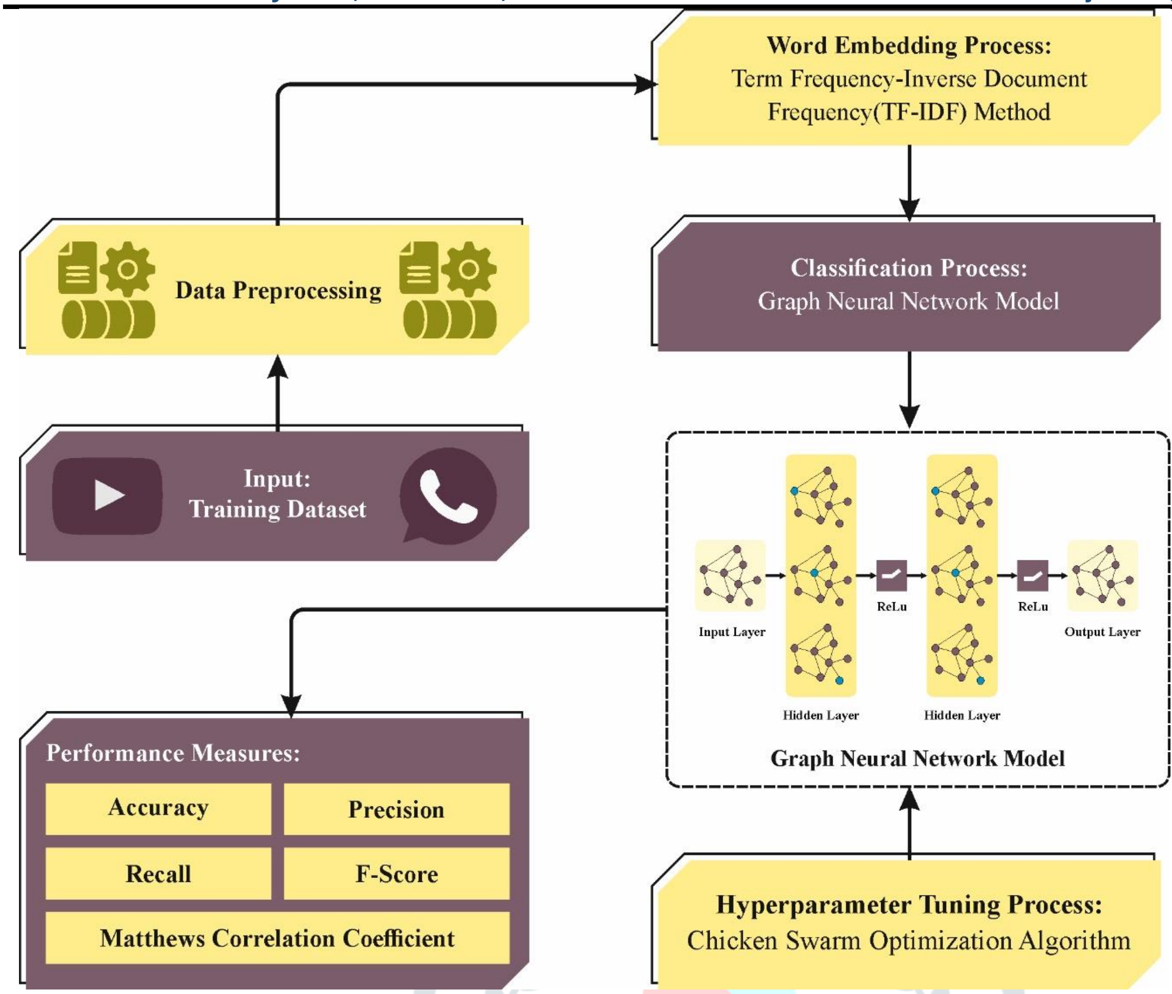

Fig. 1. Overall process of CSOA-GNN model

2.2. Classification using GNN model

At this stage, the CSOA-GNN model performs classification using GNN model. GNN is used for analyzing the network topology of TSN system [17]. GNN can identify central nodes, learn patterns, perform community or clustering detection, and detect anomalies within the TSN network by treating devices and connections as nodes and edges in the graph. This can provide useful data for fault detection and network optimization. Mostly, a graph is r represented by the network connected to nodes $C = \{1, 2, \ldots, c\}$ and the edges $E = 1, 2, \ldots, E$ along with notation $\mathcal{G} = (C, E)$. A mapping $C \rightarrow R$ is defined as the graph signal. $f = [f_1, f_2 \ldots f_c]^T T$ where the signal strength on vertex c is denoted as f_c.

Furthermore, the topology should be understood as vertices are closely related to architecture as follows.

$$\mathbb{A}_{ij} = \begin{cases} 1, & if\ e_{ij} \subseteq \varepsilon \\ 0, & else \end{cases} \tag{1}$$

Where e_{ij}represents the edge between C_I and C_J. C_J indicates $C_I{}'s$ neighbor in the meantime:

$$\mathbb{D}_{ij} = \sum_j \mathbb{D}_{ij}. \tag{2}$$

Thus, $L = D = A$ defines the Laplacian matrix.

$$\mathbb{L}_{ij} = \begin{cases} |num(C_i)|, if\ i = j \\ -1, if\ e_{ij} \subseteq \varepsilon \\ 0, oTherwise \end{cases} . \tag{3}$$

Using GNN, learning issues including non-Euclidean data or graph structure can be resolved. Based on graph perception, the hidden state embedding $h_C,\ c\varepsilon\mathscr{b}$ denotes the learning objective of GNN. Especially, GNN gathers features from nearby vertices and vertex's edges to update hidden layer of vertex and it is changed at time $T + 1$:

$$h_c^{c+1} = f\left(X_c, X_c^{con(c)}, X_c^{nei(c)}, X_{nei(c)}^c\right), \tag{4}$$

In Eq. (4), $f(.)$ refers to the Local Transaction Function, $x_c^{con(c)}$ denotes the property of edges next to vertex $c, x_c^{nei(c)}$ shows the property of vertex's neighbors, $\hbar_{nei(c)}^t$ indicates the characteristics of vertex c's neighbors.

The fitting function $(.)$ set up as essential and makes various types of GNN namely Graph Spatial-Temporal Networks, Graph Generative Networks, and Graph Autoencoder.

2.3. CSOA based parameter tuning

Finally, the hyperparameter tuning process is exploited by using the CSOA. CSOA is stimulated by the foraging strategy of flock and maps these behaviors to mathematics [18]. For ease, the chicken behavior is discussed below.

- A chicken swarm is separated into small clusters. Each cluster has rooster, numerous chicks and hens.
- The chickens and the separation of clusters are recognized using the fitness value. Many chickens with optimum fitness value are nominated as roosters, and every rooster is employed as the leader. But for some chicks with worst fitness value, the remaining are recognized as hens.
- The dominance, hierarchy and mother-child relations are upgraded every few (G) iterations.
- The rooster performs as a leader while hunting for food. Assume chicken steals food at random from every other. Chicks hunt for food near the mother.

Assume $rNum, hNum, cNum$ and $mNum$ corresponds to the amount of roosters, chickens, chickens and mother hens, correspondingly. For the issue of improving minimization, $mNum$ chickens are arbitrarily chosen as mother hens. $rNum$ chickens with low fitness values are supposed to be roosters, the worst $cNum$ chicken is measured to be chicks and remaining chickens are measured as hens. N chickens are signified by their locations $x_{i,j}^t, (i \in [1, \dots, N], j \in [1, \dots, D])$ at time t, exploring food within search range.

Dissimilar members of the swarm travel inversely:

$$x_{i,j}^{t+1} = x_{i,j}^{t}\left(1 + Randn(0, \sigma^2)\right) \tag{5}$$

$$\sigma^2 = \begin{cases} 1, & if f_i \le f_k \\ exp\left(\frac{f_k - f_i}{|f_i| + \epsilon}\right), & otherwise \end{cases}, k \in [1, RN], k \ne i. \tag{6}$$

Here $Randn(O, \sigma^2)$ signifies a random amount produced from Gaussian distribution with mean 0 and variance σ^2. k denotes the index of rooster chosen randomly and f_k is its corresponding fitness value. ε represents the least constant included to evade a zero denominator.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + C_1 Rand\left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + C_2 Rand\left(x_{r2,j}^{t} - x_{i,j}^{t}\right), \tag{7}$$

$$\begin{cases} C_1 = exp\left(\frac{f_i - f_{r1}}{|f_i| + \epsilon}\right) \\ C_2 = exp(f_{r2} - f_i) \end{cases} \tag{8}$$

where $Rand$ denotes the random number produced from an even distribution following [0,1], $r1$ refers to the index of the mate in the cluster and its fitness value is f_{r1}. Besides, an individual arbitrarily nominated from the cluster of roosters and hens is $r2$:

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL\left(x_{m,j}^{t} - x_{i,j}^{t}\right), \tag{9}$$

where m signifies the index of the mother hen and $x_{m,j}^{t}$ indicates the mother hen location of the i^{th} chick in the j^{th} dimension. FL represents the parameter preferred from [0 and 2] that signifies the influence factor of the mother hen's location.

The fitness selection is the key factor which influences the performance of CSOA technique. The hyperparameter selection method contains the solution encoding method to evaluate the efficiency of candidate solutions. Here, the CSOA model considers accuracy as a main criterion for designing the FF.

$$Fitness = \max(P) \tag{10}$$

$$P = \frac{TP}{TP + FP} \tag{11}$$

Where TP and FP are the true positive and false positive values.

3. Performance validation

In this study, the sarcasm detection results of the CSOA-GNN method are tested on the Kaggle dataset [19]. The dataset includes 1956 samples with two classes as defined in Table 1.

Table 1 Details of dataset

Class	**No. of Samples**
Sarcastic	308
Non Sarcastic	1648
Total Number of Samples	**1956**

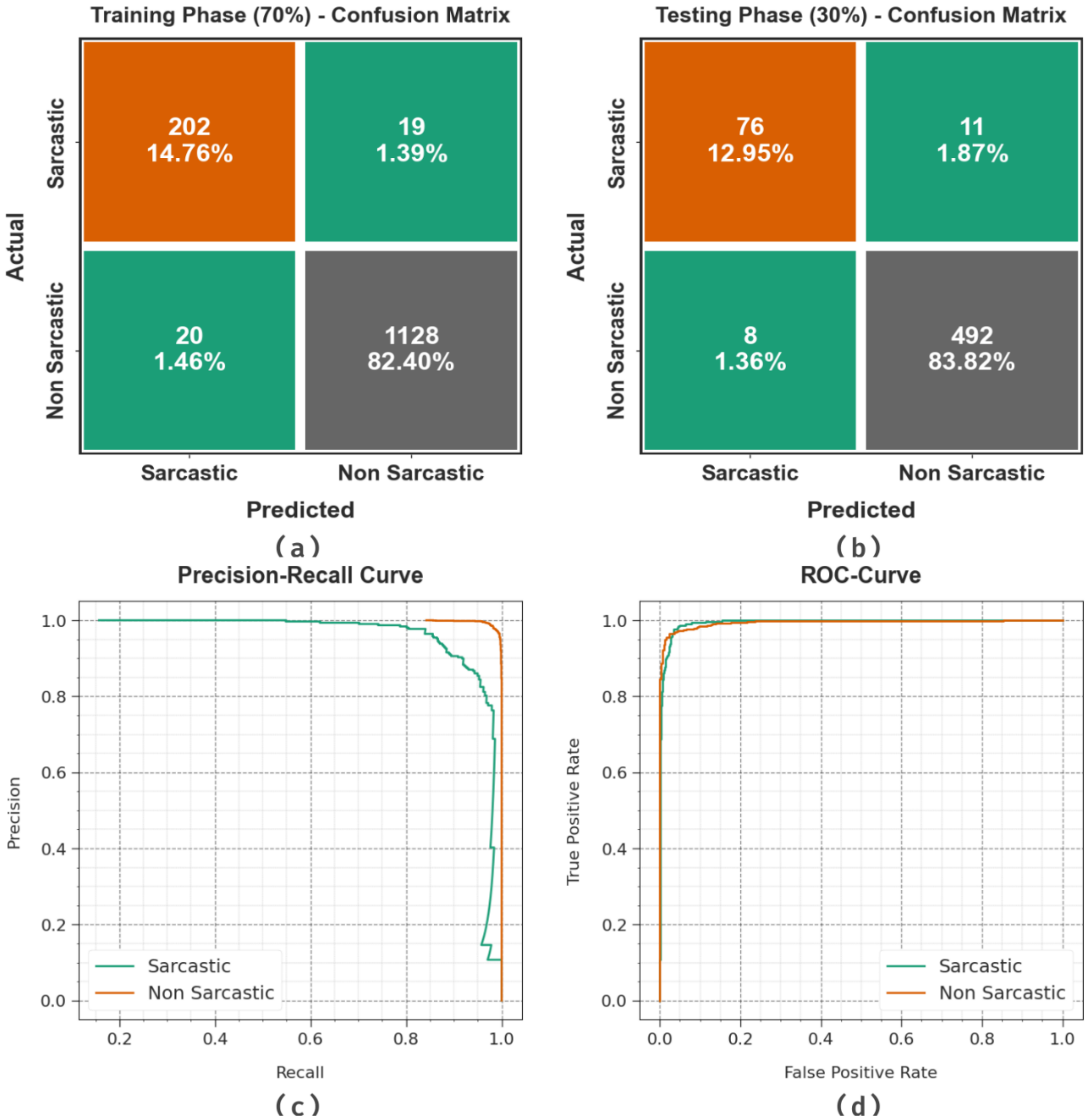

Fig. 2. Classifier outcome of (a-b) Confusion matrices and (c-d) PR and ROC curves

The classifier outcomes of the CSOA-GNN method under test dataset are demonstrated in Fig. 2. The confusion matrix presented by the CSOA-GNN technique on 70:30 of TRPH/TSPH is shown in Figs. 2a-2b. The figure indicated that the CSOA-GNN approach has accurately detected and categorized 16 class labels. Likewise, Fig. 2c demonstrates the PR analysis of the CSOA-GNN model. The figure indicates that the CSOA-GNN algorithm has gained high PR performance under all classes. At last, the ROC investigation of the CSOA-GNN model is shown in Fig. 2d. The figure shows that the CSOA-GNN algorithm has resulted in proficient outcomes with high ROC values under various class labels.

The sarcasm recognition results of the CSOA-GNN model are demonstrated in Table 2 and Fig. 3. With 70% of TRPH, the CSOA-GNN model gains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 94.83%, 94.67%, 94.83%, 94.75%, and 89.50%, respectively. Also, with 30% of TSPH, the CSOA-GNN model gains average $accu_y$, $prec_n$, $reca_l$, F_{score}, and MCC of 94.83%, 94.67%, 94.83%, 94.75%, and 89.50%, correspondingly.

Table 2 Sarcasm recognition outcome of CSOA-GNN model on 70:30 of TRPH/TSPH

Classes	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}	MCC
Training Phase (70%)					
Sarcastic	91.40	90.99	91.40	91.20	89.50
Non Sarcastic	98.26	98.34	98.26	98.30	89.50
Average	**94.83**	**94.67**	**94.83**	**94.75**	**89.50**
Testing Phase (30%)					
Sarcastic	87.36	90.48	87.36	88.89	87.01
Non Sarcastic	98.40	97.81	98.40	98.11	87.01
Average	**92.88**	**94.14**	**92.88**	**93.50**	**87.01**

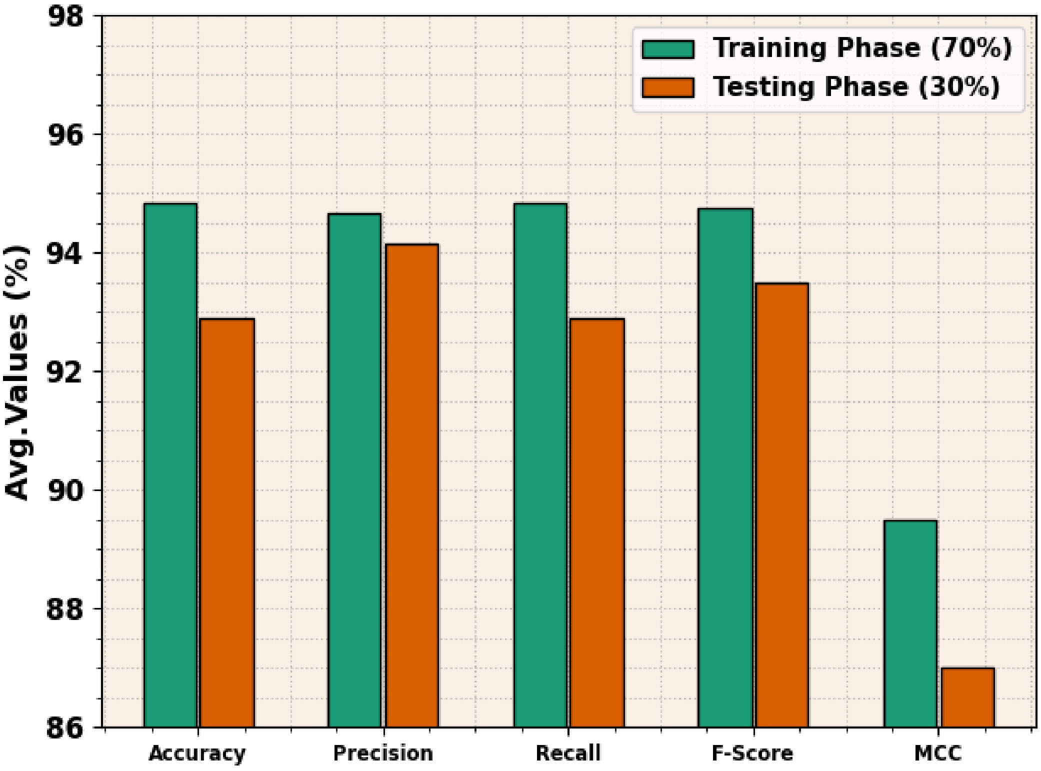

Fig. 3. Average of CSOA-GNN model on 70:30 of TRPH/TSPH

In Table 3, the results of the CSOA-GNN technique undergo comparison with other recent models [20].

In Fig. 4, a comparative $accu_y$ and $prec_n$ results of the CSOA-GNN technique are given. The results indicate that the Vanilla-CNN model reaches worse results with the lowest values of $accu_y$ and $prec_n$. Next, the ELMo-BiLSTM and ELMo-BiLSTM FULL models obtain closer values of $accu_y$ and $prec_n$. Although the fracking sarcasm and A2Text-Net models reach reasonable values of $accu_y$ and $prec_n$, the proposed CSOA-GNN model has gained maximum $accu_y$ and $prec_n$ of 94.83% and 94.67%, correspondingly.

Table 3 Comparative analysis of CSOA-GNN algorithm with other methods

Methods	$Accu_y$	$Prec_n$	$Reca_l$	F_{Score}
CSOA-GNN	94.83	94.67	94.83	94.75
Vanilla-CNN	72.63	71.48	67.76	68.88
Fracking Sarcasm	90.15	88.74	88.63	88.54
ELMo-BiLSTM	77.06	76.34	75.77	76.13
ELMo-BiLSTM FULL	78.49	78.02	74.22	75.99
A2Text-Net	93.39	92.41	91.47	90.53

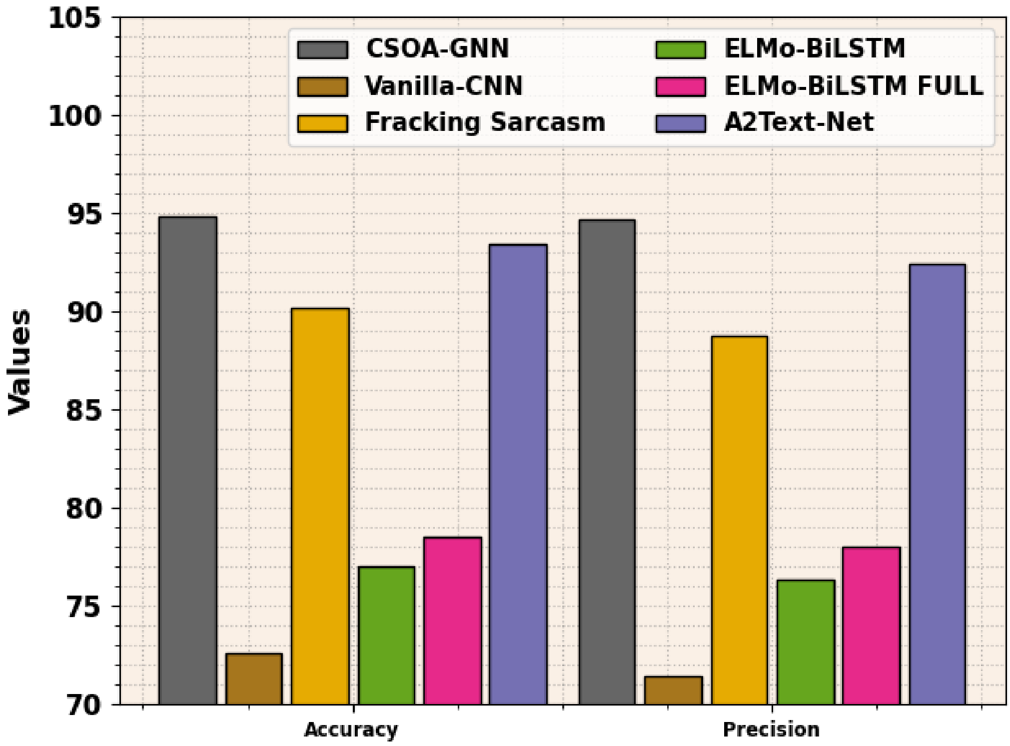

Fig. 4. $Accu_y$ and $prec_n$ analysis of CSOA-GNN technique with other models

A comparative $reca_l$ and F_{score} results of the CSOA-GNN technique are given in Fig. 5. The outcome indicated that the Vanilla-CNN technique obtains worse outcomes with minimum values of $reca_l$ and F_{score}. Next, the ELMo-BiLSTM and ELMo-BiLSTM FULL techniques attain closer values of $reca_l$ and F_{score}. Although the fracking sarcasm and A2Text-Net approaches reach reasonable values of $reca_l$ and F_{score}, the proposed CSOA-GNN technique has obtained highest $reca_l$ and F_{score} of 94.83% and 94.75%, correspondingly. Therefore, the CSOA-GNN model is found to be promising over existing ones.

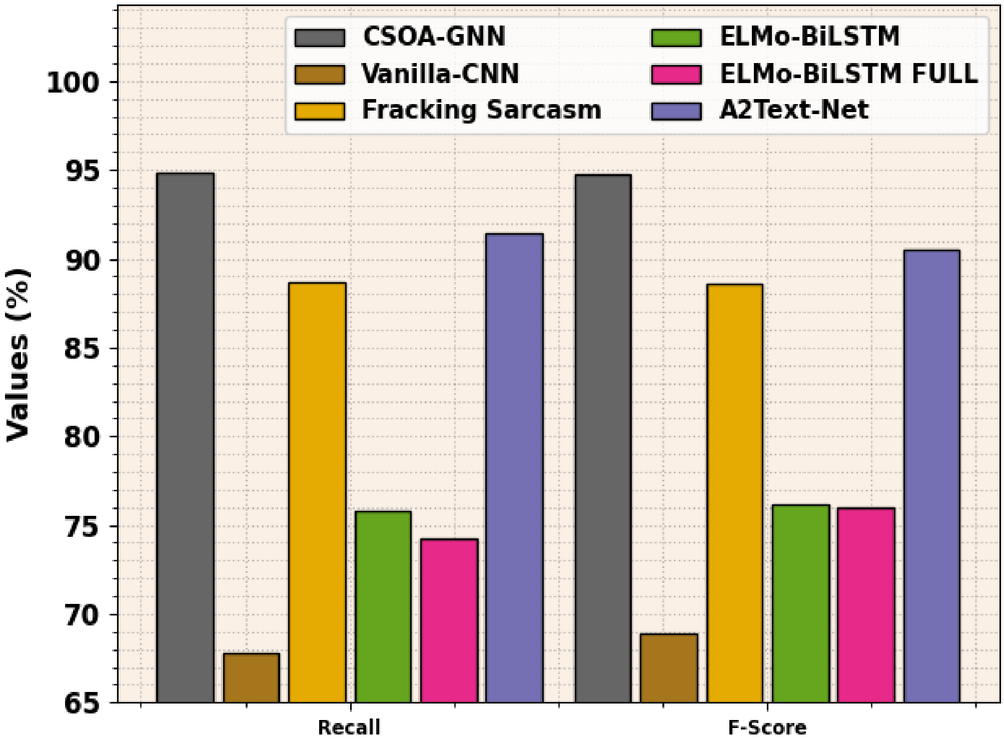

Fig. 5. $Reca_l$ and F_{score} analysis of CSOA-GNN technique with other models

4. Conclusion

In this paper, we have presented an innovative technique to enhance sarcasm detection by integrating the CSOA-GNN model. The CSOA-GNN technique's main purpose is to contain different processes namely data preprocessing, GNN-based classification, and CSOA-based parameter tuning. Firstly, data preprocessing takes place and TF-IDF is exploited for word embedding, which captures the distinct features of sarcastic language in a vectorized representation. Then, the GNN is applied for classification, using its capability to capture contextual relationships and dependencies amongst words in sentences, thus enhancing the model's sarcasm detection performance. Furthermore, CSOA is introduced for parameter tuning, improving the GNN's hyperparameter to refine its performance. This new integration contributes to the development of NLP technique for better understanding and interpretation of sarcasm in online interaction.

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